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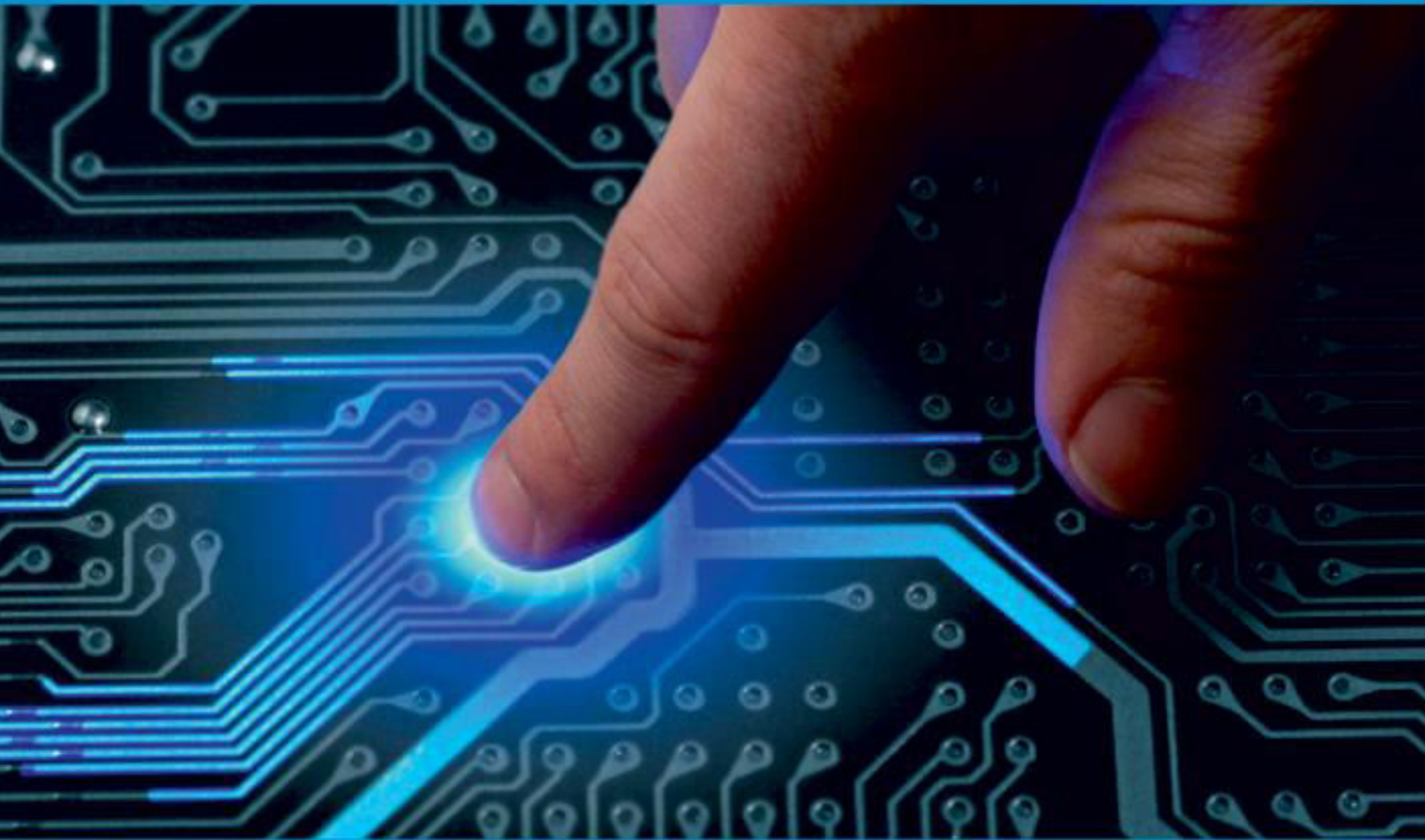

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Facial Authentication Using MTCNN and Face Net Embeddings

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ABSTRACT: A system called facial authentication uses face recognition to confirm a person's identification. Using the MTCNN (Multi-task Cascaded Convolutional Neural Network) method for face detection and FaceNet embeddings for face recognition, we suggest a facial authentication system in this study. The suggested system first uses the MTCNN method to identify the faces in an input image before utilising the FaceNet model to produce high-dimensional embeddings. The identity of the user is subsequently verified by comparing these embeddings to those of a previously registered user. Our findings show that the suggested method is a viable option for face authentication and has promise for use in practical settings like mobile device authentication and secure access control systems.

KEYWORDS: Machine Learning, Facial Authentication, Dataset, MTCNN and FaceNet Embeddings.

I. INTRODUCTION

Brain tumor is the growth of tissue in the brain which contains abnormal cells. As per statistics it is estimated that atotal of 11,700 people is dying per year due to the brain tumor. So, the early detection of brain tumors is much moreessentialtosavemore lives.

We used the Convolution Neural Network (CNN) algorithm to build a model with 3 layers which takes input of Magnetic Resonance Imaging (MRI) scan images and detects whether the person hasatum or or not.

II. RELATEDWORK

1.S.T. Gandhe has explored how to use various implementations of the facial recognition technology to mark the five moles. This approach essentially depicts and suggests several applications, including document management, access control, and identity systems.

2.Jalendu Dhamija et al. developed three techniques called Principle Component Analysis (PCA), Single Vector Decomposition (SVD), and Fisherface in their article "An Advancement towards Efficient Face Detection utilising Live video stream," where face recognition rate is correct by combining them.

3.Fatima Sartaj Khan, Praveen Kumar, and Aayush Mittal have concentrated on automating the conventional method of collecting attendance by keeping paper copies of the records and integrating themechanism to make all of the records accessible in order to prevent mistakes. This technique demonstrates how to record attendance for several students in a classroom within a single attempt. As compared to the alternatives, our approach proved to be more accurate.

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4.Setia Budi et al. [1] have suggested a relatively low-cost method for taking pictures of students seating in a classroom. Using a camera, the image is taken and sent to a server, which then uses a face identification algorithm to automatically locate and define the region of each student's face.

III. PROPOSED ALGORITHM

This system was developed using MTCNN and FacNet Embeddings.

FaceNet Embeddings

Schroff et al. presented FaceNet, a deep learning network for facial recognition, in 2015. FaceNet's architecture is made up of three key parts:

1.Convolutional Neural Network (CNN): From an input picture, the CNN derives a feature vector that, in a high-dimensional space, represents the face. Convolutional, max-pooling, and local response normalisation layers make up the nine layers of the CNN network. The network has been trained to maximise both the similarity of face embeddings for faces that match and the dissimilarity of face embeddings for faces that don't match.
2.Triplet Loss Function: The CNN is trained to provide semantically relevant face embeddings using the triplet loss function. The loss function contrasts the distance between the anchor and negative picture with the distance between the anchor and positive image, which is an image of the same person as the anchor (an image of a different person). The embeddings are encouraged to be close for matching faces and distant for non-matching faces by the loss function.
3.Embedding Layer: The CNN's embedding layer produces a 128-dimensional feature vector as its last layer output, which depicts the face in a high-dimensional space. The "facial embedding" feature vector is what is utilised to identify faces. The high-dimensional input picture is taught to be mapped into a lower-dimensional space by the embedding layer, where the distances between the embeddings represent the similarity between the faces.

MTCNN
In 2016, Zhang et al. introduced the deep learning-based face identification system known as MTCNN (Multi-Task Cascaded Convolutional Neural Network). The method is made up of three cascading steps, each of which completes a certain function in the face identification process. There are three phases:

The initial stage of MTCNN is called the **Proposal Network (P-Net)**, and it is in charge of producing a lot of candidate areas (also known as proposals) in an input picture. It produces a series of bounding box recommendations for potential faces in the input image using a fully convolutional neural network.

Refinement Network (R-Net): The P-Net produced candidate areas are refined in the second stage of MTCNN. Moreover, it is a fully convolutional neural network that receives input from the candidate areas and generates precise bounding boxes and confidence values for each prospective face.

The third and last stage of MTCNN, known as the **Output Network (O-Net)**, is in charge of further optimising the bounding boxes and creating face landmarks. It is a fully convolutional neural network as well, and it produces the final bounding boxes as well as five facial landmarks for each recognised face after using the R-refined Net's bounding boxes as input.

By removing false positives at each layer, MTCNN's cascaded design enables more precise face detection. MTCNN is a strong face identification method since it can handle faces with various sizes and orientations.

IV.PSEUDO CODE

For MTCNN

1. Load the supplied picture
2. Prepare the source picture (normalize pixel values, resize to a specific size, etc.)
3. Use P-Net to create candidate face areas from the preprocessed picture (bounding boxes)
4. Use NMS (non-maximum suppression) to eliminate candidate areas that overlap.
5. Refine the bounding boxes by resizing the remaining potential regions and sending them to R-Net.
6. Reapply NMS to eliminate potential locations that overlap.
7. Enlarge the final potential areas and send them to O-Net for facial landmark extraction (eye, nose, and mouth coordinates)

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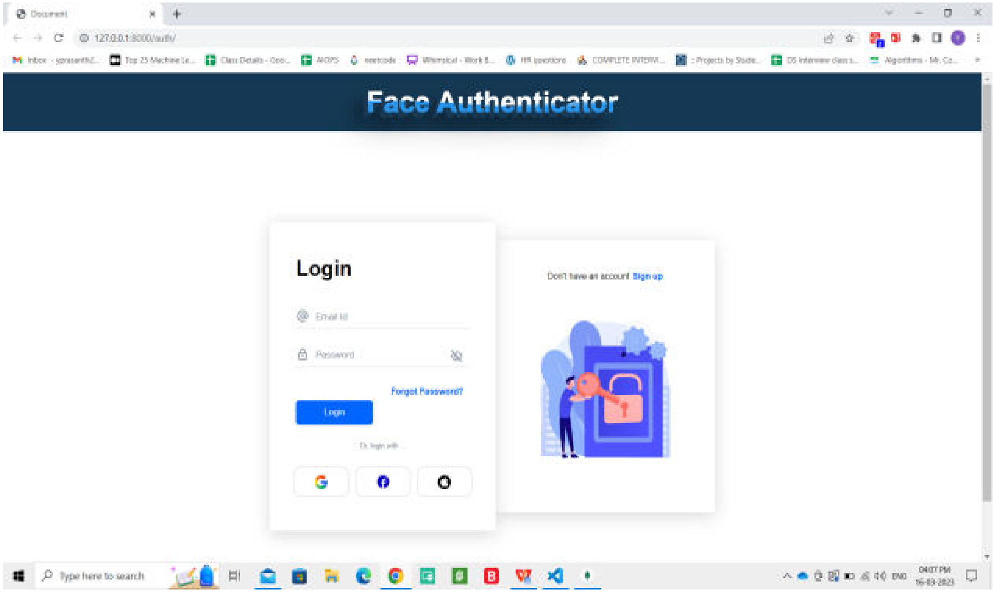
8. Provide the last set of facial landmarks and bounding boxes for each discovered face.

For FaceNet Embeddings

1. Add a trained FaceNet model.
2. Upload and prepare a facial picture (normalize pixel values, resize to a specific size, etc.)
3. Use the FaceNet model to create a feature vector for the face by running the preprocessed picture through it.
4. Repetition of steps 2 and 3 for each face that requires comparison
5. To determine how similar a pair of faces are to one another, compute the Euclidean distance between their feature vectors.
6. The final similarity scores and identity labels for all face pairings are returned after setting a threshold for the similarity score to decide whether two faces are identical or not.

IV.EXPERIMENTAL RESULT



Login Page

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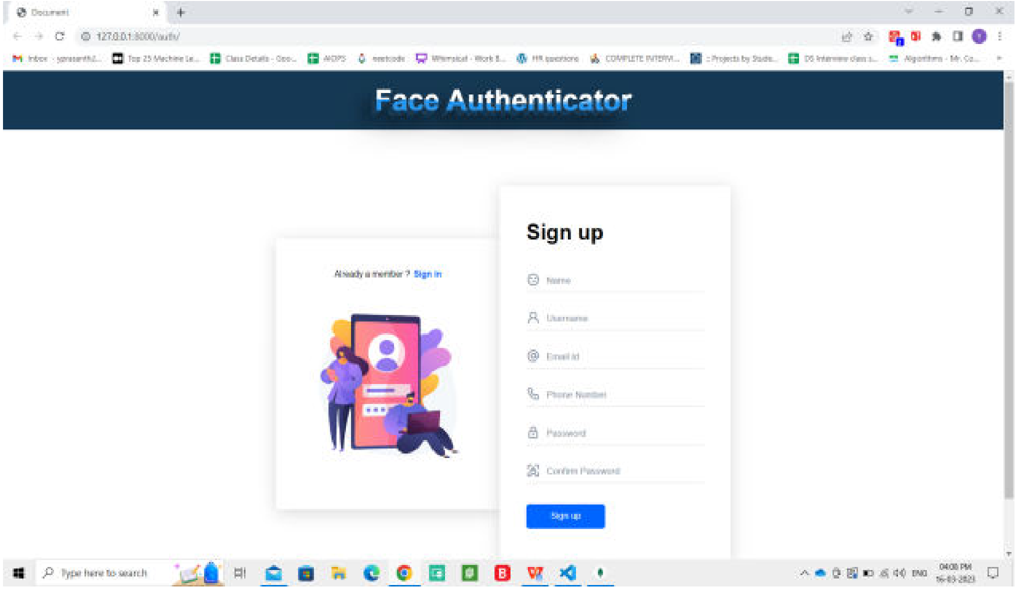
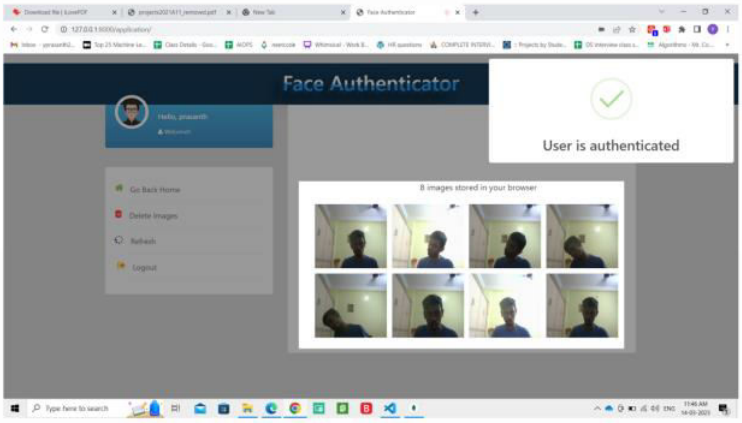


Registration Page



OUTPUT

The accuracy and dependability of face recognition systems have significantly improved as a consequence of facial authentication employing MTCNN and FaceNet embeddings. The system can recognise and extract faces at various sizes and orientations, as well as create high-dimensional embeddings that capture the individual aspects of the face, thanks to the usage of deep learning techniques like MTCNN and FaceNet. These findings show that the suggested approach has potential as a safe access control and mobile device authentication mechanism.

IV. CONCLUSION

In conclusion, deep learning based Convolutional Neural Networks (CNNs) have shown promising results in detecting brain tumors. This CNN model takes in MRI images of the brain and processes them through multiple convolutional layers to extract features, which are then classified as either tumor or non-tumor. Our model's overall accuracy is 98%.The output of this CNN model is a binary classification, with 1 indicating the presence of a tumor and 0 indicating itsabsence. This output can help healthcare professionals make informed decisions about treatment options and provide better care topatients.

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